Analysing User Experience of Mobile Banking Applications in Nigeria: A Text Mining Approach

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This paper analyses textual data mined from 37,460 reviews written by mobile banking application users in Nigeria over the period November 2012 – July 2020. On a scale of 1 to 5 (5 being the best), the average user rating for the twenty-two apps included in our sample is 3.5; with the apps deployed by non-interest banks having the highest average rating of 4.0 and those by commercial banks with national authorisation having the least rating of 3.4. Results from the sentiment analysis reveal that the share of positive sentiment words (17.8%) in the corpus more than double that of negative sentiment words (7.7%). Furthermore, we find that about 66 per cent of the emotions expressed by the users are associated with 'trust', 'anticipation', and 'joy' while the remaining 34 per cent relate to 'surprise', 'fear', 'anger', and 'disgust'. These results imply that majority of the users are satisfied with their mobile banking experience. Finally, we find that the main topics contained in the user reviews pertain to (i) feedback on banks' responsiveness to user complaints (ii) user experience regarding app functionalities and updates, and (iii) operational failures associated with the use of the apps. These results highlight the need for banks to continue to promote awareness of existing functionalities on their apps, educate users on how those solutions could be accessed, and respond to user feedback in a timely and effective manner.

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JEL classification: C46, C55, D14, D18, E44, E58, G20
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1.0 Introduction

The deployment of mobile banking and payments applications has recorded tremendous growth over the years. This is due to several reasons, including increased mobile phone penetration; financial inclusion efforts of governments; and the demand for more efficient means of payments by financial market participants (Patnam &

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Yao, 2020; Aron, 2018; Mbiti & Weil, 2015). Also, the limited availability of physical infrastructure for effective conventional banking activities provides an impetus for rapid adoption of digital financial services in developing countries. According to Global System for Mobile Communication Association (GSMA, 2019), the total number of mobile money accounts registered worldwide increased to about 1.0 billion in 2019 from 29.3 million a decade earlier, with sub-Saharan Africa accounting for about half of the registrations. In 2019, the value of daily transactions via mobile accounts stood at about US$2 billion, as households and firms relied predominantly on digital payments for transactions relating to school fees, e-commerce, international remittances, savings, credit, pay-as-you-go utilities, among others (GSMA, 2019). According to Total System Services (TSYS, 2018), many bank customers also use mobile banking app for non-transactional purposes, such as checking account balance and viewing recent transactions.

Mobile payments refer to the category of financial transactions conducted using access devices that are enabled by mobile communication networks (Committee on Payment and Settlement Systems [CPSS], 2012). These transactions are often initiated and transmitted over mobile communication protocols like Short Message Services, mobile applications, web browsers for mobile phones, Near Field Communications, and Quick Response Codes (Khiaonarong, 2014). The funds utilised under mobile payment arrangements are sourced from linked accounts, which may either be (i) customer funded bank accounts, or (ii) customer stored-value funds maintained by mobile network operators (CPSS, 2012). Thus, the ecosystem for digital financial services is managed by a number of critical stakeholders including: banks; telecommunication companies; and third party software companies (Castle *et al.,* 2016).

In Nigeria, the size of mobile payments has risen dramatically over the last few years in response to global, domestic, market, technological, and regulatory factors. Data from the Nigeria Interbank Settlement System (NIBSS) show that while the volume of mobile transactions was 51 million in 2017, it reached 410 million in 2019 representing a growth of about 703.9 per cent (see Figure 1a). Similarly, the value of mobile transactions increased sharply from N196.3 billion in 2017 to N828.1 billion in 2019. The value of mobile transactions (N853.7 billion) recorded in the first five months of 2020 surpassed the total amount recorded in 2019 by 3.1 per cent. The phenomenal growth in the value of mobile payments, especially in May 2020 (Figure 1b) can be partly explained by the effects of the restricted human movements associated with the lockdown measures implemented in response to the Covid-19 pandemic.

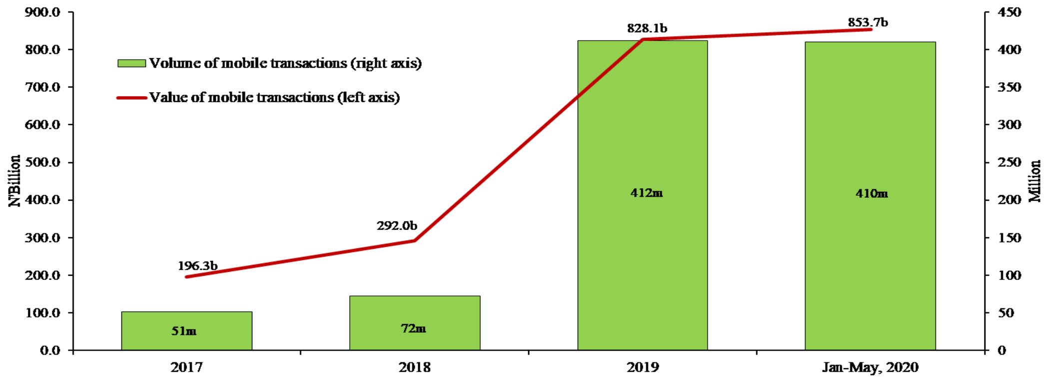

Figure 1a: Annual volume and value of mobile transactions, 2017-2020.
Source: Nigeria Inter-Bank Settlement System Plc.

The increasing relevance of mobile payments as a share of global financial transactions presents financial authorities with the added responsibility of ensuring consumer protection as well as payment system efficiency and safety on such platforms. Khiaonarong (2014) provides a detailed account of relevant legal and regulatory interventions that have been implemented in different countries, including explicit mobile payment regulations. Examples of such regulations are the Da Afghanistan Bank Money Service Providers Regulation of 2008; the Reserve Bank of India's Operative Guidelines for Mobile Banking Transactions of 2011; the Bank of Uganda's Mobile Money Guidelines of 2013; the Central Bank of Brazil's Law 12865 of 2013; and the Central Bank of Nigeria's Guidelines on Mobile Money Services of 2015 as well as the associated regulatory framework.

The literature on mobile money services is still at its infancy, with the existing studies focusing on regulatory oversight and security issues in mobile banking and payments (Khiaonarong, 2014; Reaves *et al.,* 2017); the economic impacts of mobile money services (Patnam & Yao, 2020; Wieser *et al.,* 2019); determinants of mobile banking adoption (Khan & Ejike , 2017; Agwu & Carter, 2014); and the analysis of user experience (Olaleye *et al.,* 2017). Of these, an area that has received little attention in literature relates to the analysis of feedback provided by bank customers on their experiences with digital financial applications. This area of research is important for a number of reasons. First, it helps to draw the attention of mobile banking and payments apps providers to operational issues being faced by their customers and users. Second, it helps banks gauge the extent to which customers are adopting their services. Third, it helps financial regulators detect factors that could potentially threaten payments and financial system stability and financial inclusion efforts.

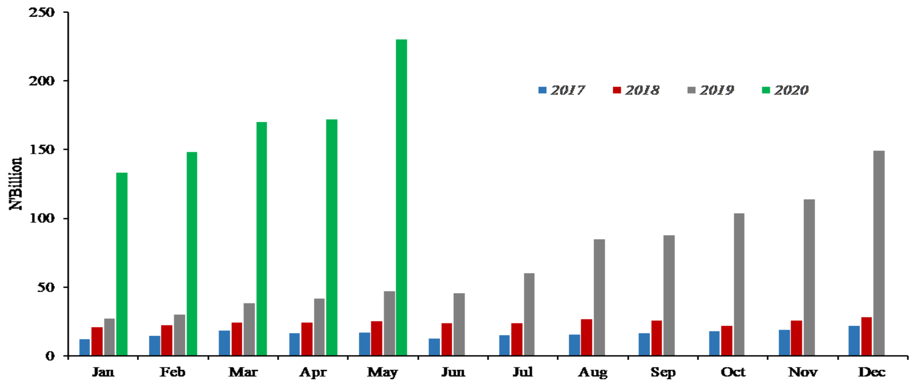

Figure 1b: Monthly value of mobile transactions, January 2017 – May 2020.
Source: Nigeria Inter-Bank Settlement System Plc

This study analyses the experiences of users of mobile banking applications in Nigeria. In contrast to existing studies on Nigeria that are based on the analysis of survey returns, this study applies text mining techniques to textual data mined from the reviews written by mobile banking application users. The study finds this approach appealing for several reasons. First, it allows for the use of information from a wider spectrum of mobile banking apps users in a less costly manner. Second, compared to returns from structured questionnaires, it allows for the analysis of a wider range of issues as all the issues raised by users in their reviews are considered. Third, it allows us to detect the key topics, sentiments, and emotions expressed in the user reviews. In addition, the hidden topics in the reviews are identified using the Latent Dirichlet Allocation (LDA) modelling approach. To our knowledge, this study represents the first attempt in this direction for Nigeria. This effort is in line with the G20 principles for innovative financial inclusion, which support the creation of knowledge to enhance the versatility of digital financial services provisioning (Access through Innovation Sub-Group, 2010).

The rest of the paper is laid out as follows: Section 2 provides a review of related literature. Section 3 describes the text mining procedures used for the analysis. In Section 4, the results are presented and discussed. Section 5 provides some concluding remarks and policy recommendations.

2.0 Literature Review

The literature on mobile money services can be categorised under four major strands (Appendix 1). The first strand relates to regulatory oversight and security issues in mobile banking and payments (Contini *et al.,* 2011; Chatain *et al.,* 2011; Khiaonarong, 2014; Castle *et al.,* 2016; Reaves *et al.,* 2017). For instance, Khiaonarong (2014) argued that countries with relatively high deployments of mobile payments would benefit from the implementation of oversight measures aimed at ensuring that such digital invention does not disrupt payment and financial system stability. It is argued that, among others, financial authorities can preserve public confidence in mobile payments and enhance financial stability by implementing oversight measures such as: an explicit legal regime; anti-money laundering and countering the financing of terrorism measures for preventing financial integrity risks without stifling innovation; fund protection measures such as pass through deposit insurance; contingency plans for operational disruptions; and risk controls in payment systems. According to Dittus and Klein (2011), regulatory frameworks should be designed to help achieve financial inclusion and in a manner that they can be easily amended should the growth in mobile payments becomes rapid enough to threaten financial stability. Also crucial for successful mobile banking and payments is the need for effective coordination between bank and non-bank regulators (Contini *et al.,* 2011).

The second strand focuses on the economic impacts of mobile money. Some of the economic benefits identified in the literature include increased banks' profitability (Okon & Amaegberi, 2018), higher customer satisfaction (Adewoye, 2013), enhanced financial inclusion and stability (Mbiti & Weil, 2015; Ozili, 2018; Aron, 2018; Bongomin *et al.*, 2018), reduction in cost of remittance transactions (Mbiti & Weil, 2015; Aron, 2018; Wieser *et al.,* 2019), increased banking system efficiency (Mbiti & Weil, 2015), improved resilience of households to shocks (Patnam & Yao, 2020), increased household and firm's savings (Jack & Suri, 2011; Mbiti & Weil, 2015; Aggarwal *et al.,* 2020), enhanced self-employment (Mbiti & Weil, 2015; Wieser *et al.,* 2019), trade facilitation (Jack & Suri, 2011), higher firms' sales (Patnam & Yao, 2020), reduction in food insecurity (Wieser *et al.,* 2019), promotion of informal risk sharing (Jack & Suri, 2011), and improved livelihoods especially in developing countries (Wieser *et al.,* 2019).

The third strand of the literature studies the determinants of mobile banking adoption (see Bankole *et al.,* 2011; Odumeru, 2013; Agwu & Carter, 2014; Ifeonu & Ward, 2015; Khan & Ejike, 2017). These studies, which are largely based on survey of mobile banking and payment users identify factors such as literacy level, versatility of the mobile banking system, convenience of use, culture, security, cost of transaction compared to other alternatives, complexity of the system, compatibility with the circumstances of the user, and the visibility of its benefits to users.

An area that has received little or no attention in literature relates to the analysis of feedbacks provided by bank customers on their experiences using digital financial applications. A few studies have been conducted on the adoption of mobile banking technology in Nigeria with most of them based on the administration of structured questionnaire to a limited number of respondents. For instance, Olaleye *et al.* (2017) analysed the experience of mobile money users in Nigeria using a survey of 151 respondents. It was shown that features such as security, privacy and convenience make mobile money attractive to users. Also, based on a survey of 1,725 respondents, Ifeonu and Ward (2015) found that mobile technology trust and adoption behaviour in Nigeria are driven by factors that include confidentiality, integrity, authentication, and access control. In addition to these, Odumeru (2013) conducted a survey covering 91 users of mobile banking in Nigeria and found that the complexity of the system as well as compatibility of the system with the circumstances of the user matter for mobile banking adoption. This paper relates to the literature strand analysing the experiences of mobile banking and payments apps users.

3.0 Data and Methodology

Following the definition of Barnes and Corbitt (2003) the mobile banking apps considered in this paper are those deployed by financial services providers for the purposes of offering certain transactional and non-transactional financial services to customers with bank accounts[2]. Once the app is downloaded and the sign-up as well as sign-in procedures are successfully completed, the user is granted access to their bank accounts for the purpose of conducting mobile banking activities that are permitted by the bank. In addition, the apps allow users to write reviews about their mobile banking experience and also provide quantitative ratings of the bank's performance. Such feedback constitutes an important source of information for both the app providers (the banks) and the regulatory authority.

The textual data analysed in this study comprises of reviews provided by users of mobile banking apps developed by 22 Nigerian banks. The analyses are implemented using the *R* statistical software. The downloaded reviews cover all iOS and Android mobile banking apps available on Google Play and App Store via *Heedzy*. In all, we downloaded a total of 37, 460 reviews spanning the period, November 2012 – July 2020, representing all the reviews available with *Heedzy* for the selected apps (Table 1).[3] Of these, a total of 23, 308 (representing about 62 per cent) pertain to mobile banking apps deployed by commercial banks with international authorisation (CBIA) while 13, 772 reviews pertain to apps deployed by banks with national authorisation. The remaining reviews were accounted for by commercial banks with regional authorisation (109 reviews) and non-interest banks (271 reviews).

[2] In the case of mobile payments, the user is not required to hold an account with a bank.

[3] This paper has a number of weaknesses. First, being the first attempt at analysing user reviews on mobile banking apps for Nigeria, we opted to cover all the textual data available on Heedzy.com; rather than limiting the sample to a period that is uniform across the banks. Thus, this approach reduces the ability of the paper to study the evolution of user sentiments overtime. Second, the long historical data considered in the paper for some of the banks implies that some of the concerns contained in the analysed reviews may have been overtaken by technological advancements. However, for upgrades to mobile apps that are successful in addressing certain legacy concerns, the positive sentiments associated with such improvements would have been captured in our paper.

Table 1: Distribution of downloaded reviews

Bank authorisation	Mobile application	Period	No. of reviews
Commercial Banks with International Authorisation (CBIA)	Access Bank	July 2014 - July 2020	3,108
	FCMB	March 2015 - July 2020	1,585
	Fidelity Bank	October 2015 - July 2020	2,526
	First Bank	October 2015 - July 2020	3,291
	Guaranty Trust Bank	November 2012 - July 2020	3,434
	Union Bank	January 2018 - July 2020	3,016
	United Bank for Africa	August 2015 - July 2020	3,207
	Zenith Bank	November 2013 - July 2020	3,141
	Sub-total		*23,308*
Commercial Banks with National Authorisation (CBNA)	Ecobank	July 2016 - July 2020	3,117
	Heritage bank	January 2016 - July 2020	471
	Keystone Bank	January 2018 - July 2020	1,077
	Polaris Bank	August 2019 - July 2020	915
	Stanbic IBTC	November 2016 - July 2020	2,739
	Standard Chartered	June 2013 - July 2020	1,753
	Sterling Bank	May 2018 - July 2020	3,000
	Titan Trust Bank	November 2019 - July 2020	37
	Unity Bank	November 2013 - July 2020	663
	Sub-total		*13,772*
Commercial Banks with Regional Authorisation (CBRA)	Globus Bank	November 2019 - July 2020	45
	Providus Bank	April 2019 - July 2020	43
	Suntrust Bank	September 2019 - July 2020	21
	Sub-total		*109*
Non-Interest Banks (NIB)	Jaiz Bank	June 2015 - July 2020	230
	Taj Bank	November 2019 - July 2020	41
	Sub-total		*271*
Grand total			**37,460**

Source: Compiled by the author from Heedzy.com

Following data collection, our corpus, which is a collection of the entire reviews, is subjected to a number of pre-processing steps in line with standard text mining procedures. First, we remove numbers, punctuations, white spaces, and special characters from the corpus. Second, the characters in the corpus are converted to lower case while English stop words such as ‘to’, ‘the’, ‘this’, ‘in’ are removed. The *tm_map* function of the *tm* package developed by Feinerer and Meyer (2008) is used for the data cleaning and transformation. Other common informal Nigerian terms such as ‘choi’, ‘buh’, and ‘chai’ are removed. In addition, a number of informal spelling of words such as ‘tanx’, ‘fyn’, ‘9ice’, ‘kul’ as well as contextual inconsistencies in the written reviews are corrected manually. Lastly, to ensure the terms in the corpus are uniquely identified, we stem the words in the document using the *stemDocument* argument of the *tm_map* function.

Word clouds are used to identify common terms in the corpus while analyses of sentiments and emotions are conducted to derive useful insights regarding the type of feelings and experiences that are predominant in the corpus. The sentiment analysis is implemented based on *Rsentiment*; an R statistical package developed to analyse the sentiments contained in a sentence (Bose *et al.,* 2017). Particularly, we apply the *calculate_sentiment* function to classify the words contained in our corpus to three categories – positive, neutral, and negative. The share of each category in the total number of words in the corpus is then computed to gauge the level of positivity or negativity in the reviews. It is important to note that the *calculate_sentiment* function is a unigram, rule-based approach to sentiment analysis that classifies texts in a binary sense. In other words, it uses the bag-of-words approach and calculates the sentiment score by matching the appearances of words in the textual data with pre-existing lexicons. An alternative to this approach is the use of automatic classifiers, which employ classification algorithms that are either probabilistic or non-probabilistic. We adopt the rule-based approach in this paper for its simplicity and the fact that the goal is not to develop a predictive model for classifying incoming user reviews. The study also explores the emotions expressed in the reviews using the *Syuzhet* package. This procedure classifies the emotions present in a corpus into eight categories based on the Canadian National Research Council (NRC) sentiment dictionary and computes their respective valence (Mohammad & Turney, 2010). These are emotions relating to ‘anger’, ‘anticipation’, ‘disgust’, ‘fear’, ‘joy’, ‘sadness’, ‘surprise’, and ‘trust’.

Furthermore, we compute the polarity score, which is a quantitative measure of positive or negative intent found in the tone of the reviews (Kwartler, 2017). The *polarity* function in the *qdap* library is employed for this purpose. The average polarity score ranges between -1 and 1; where a negative value indicates negative sentiment, a value of zero indicates neutral sentiment, and a positive value connotes positive sentiment. The analyses of sentiments are conducted for four categories of banks operating in the country and the results are benchmarked against the outturn for the entire sample. The bank categories are as follows: commercial banks with international authorisation (CBIA), commercial banks with national authorisation (CBNA), commercial banks with regional authorisation (CBRA), and non-interest banks (NIB).

Finally, this study analyses the hidden sub-themes in our corpus based on the Latent Dirichlet Allocation (LDA) modelling approach of Blei *et al.* (2003). The LDA is chosen for a number of reasons. First, the topics produced under the LDA is probabilistic, compared to non-probabilistic topics generated under methods such as the Latent Semantic Analysis of Deerwester *et al.* (1990). Second, it has been shown that the LDA yields superior outcomes in terms of generating semantically meaningful topics as well as assigning texts to the identified topics (Debortoli *et al.,* 2016; Chang *et al.,* 2009). Third, it has been used extensively in different applications, including Tumala and Omotosho (2019) for monetary policy communication in Nigeria; Omotosho (2020) for monetary policy communication in Ghana; and Hansen *et al.* (2018) for monetary policy communication in the US. More importantly, the LDA allows not only for identifying the hidden topics, but also to estimate the degree to which each topic is reflected in the corpus.

The LDA is a generative probabilistic process that is based on the assumption that each document consists of a mixture of topics, and each topic is a distribution over a given number of words (Shirota *et al.,* 2015). Following the works of Calvo-González *et al.* (2018); Shirota *et al.* (2015); Blei and Lafferty (2009); and the definitions in Blei *et al.* (2003), a word is defined as an item in a vocabulary indexed by $\{1, \ldots\ldots, V\}$. Also, a document **w** is given by an array of *N* words such that $\mathrm{w} = (w_1, \ldots, w_N)$ while a corpus represents a collection of *M* documents such that $D = (\mathrm{w}_1, \ldots, \mathrm{w}_M)$.

For each document **w**, the generative process assumed by the LDA proceeds in the following steps:

Step 1: Choose $N \sim Poisson(\varepsilon)$

Step 2: Choose $\theta \sim Dir(\alpha)$

Step 3: For each word w_n, draw a topic assignment $z_n \sim Multinomial\ (\theta)$ and also choose a word w_n from a multinomial probability conditioned on the topic z_n given by $p(w_n|z_n,\ \beta)$. β represents the parameter of the Dirichlet prior on the per-topic word distribution while α is the parameter of the Dirichlet prior on the per-document topic distribution. For the given parameters α and β, the joint distribution of θ, z and w is as follows:

$$p(\theta,z,\ \mathrm{w}|\alpha,\beta) = p(\theta|\alpha)\prod_{n=1}^{N} p(z_n|\theta)\,p(w_n|z_n,\beta). \tag{1}$$

The marginal distribution of a document is obtained by integrating over θ and summing over z as follows:

$$p(\ \mathrm{w}|\alpha,\beta) = \int p(\theta|\alpha)\left(\prod_{n=1}^{N}\sum_{z_n} p(z_n|\theta)\,p(w_n|z_n,\beta)\right)d\theta, \tag{2}$$

while the probability of a corpus is derived by taking the product of the marginal probabilities of the single documents as follows:

$$p(\ D|\alpha,\beta) = \prod_{d=1}^{M}\int p(\theta_d|\alpha)\left(\prod_{n=1}^{N_d}\sum_{z_{dn}} p(z_{dn}|\theta_d)\,p(w_{dn}|z_{dn},\beta)\right)d\theta_d. \tag{3}$$

Given a document and the Dirichlet priors, the LDA computes the posterior distribution of the hidden variables as follows:

$$p(\theta,z|\mathrm{w},\alpha,\beta) = \frac{p(\theta,z,\ \mathrm{w}|\alpha,\beta)}{p(\ \mathrm{w}|\alpha,\beta)} \tag{4}$$

Thus, we are able to find the distribution of words over each topic as well as the mixture of topics driving each document. Since calculating the maximum likelihood for equation (4) is computationally costly and sometimes intractable, it is often approximated using the Collapsed Gibbs sampling algorithm (Calvo-González *et al.,* 2018).

This paper employs the *lda* package (Chang & Dai, 2015), which implements the LDA using the collapsed Gibbs sampling methods to model the topics in the corpus.

4.0 Results and Discussion

In this section, we present the results relating to the analyses of the quantitative ratings as well as the qualitative comments provided by bank customers while using their mobile banking apps. The ratings are analysed using averages and percentage shares while text mining techniques are applied to the qualitative comments. Generally, we consider results for the full sample, which comprises reviews on apps deployed by 22 commercial banks operating in Nigeria. The list of banks in our sample with their authorisation category is provided in Table 1.

4.1 Analysis of User Ratings

Table 2 presents the average rating assigned by users, with the rating ranked from 1 to 5. The value 1 represents the least rating while the best rating is ranked 5. The average user rating for the 37, 460 reviews analysed over the period December 2012 - July 2020 is about 3.54. This tends to suggest that most users were relatively satisfied with their mobile banking apps. Furthermore, the average user rating for the different categories of banks operating in the country is computed. At average values of about 3.6 and 4.0, the results for commercial banks with international authorisation (CBIA) and non-interest banks (NIB) show ratings that are above the average for the full sample. On the other hand, commercial banks with national and regional authorisations show ratings that are below the average.

Table 2: Average user rating by bank authorisation category

Bank authorisation	No. of reviews analysed	Average user rating
Commercial Banks with International Authorisation (CBIA)	23,308	3.6038
Commercial Banks with National Authorisation (CBNA)	13,772	3.4154
Commercial Banks with Regional Authorisation (CBRA)	109	3.4678
Non-Interest Banks (NIB)	271	4.0000
Total	37,460	3.5370

Figure 2 shows the distribution of the sample across the different user ratings. Of the 37, 460 mobile app users , about 51 per cent gave the best rating of 5 while about

27 per cent assigned the least rating of 1. Overall, about 61 per cent of the bank customers assigned ratings above the sample average of 3.54 shown in Table 2. The results confirm the typical u-shaped rating for mobile applications identified by Fu *et al.* (2013). The qualitative comments driving these ratings are analysed in the subsequent sections using text mining techniques.

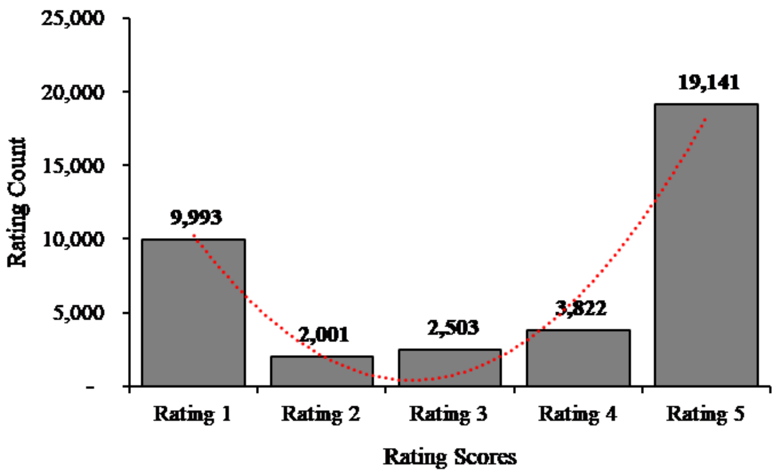

Figure 2: Distribution of user ratings

4.2 Word Frequency

Figure 3 shows a plot of the most common terms and their frequencies. The word with the highest frequency is 'good', occurring about 6, 580 times. This is followed by the term 'use', which occurred 4, 018 times. Other top frequent terms include 'can't', 'update', 'work', 'transaction', 'bank', 'try', 'please', 'great', 'nice', 'time' 'login', etc. To a large extent, these terms express sentiments regarding user satisfaction as well as the practical issues encountered while using the apps. The preponderant use of the term 'good' tend to suggest that most users consider the mobile banking apps good enough for the purposes for which they were downloaded. Also, Figure 3 shows that the term 'can't' which occurred 3, 809 times may be indicative of the inability of some users to effectively enjoy certain permissible banking services on their mobile apps.

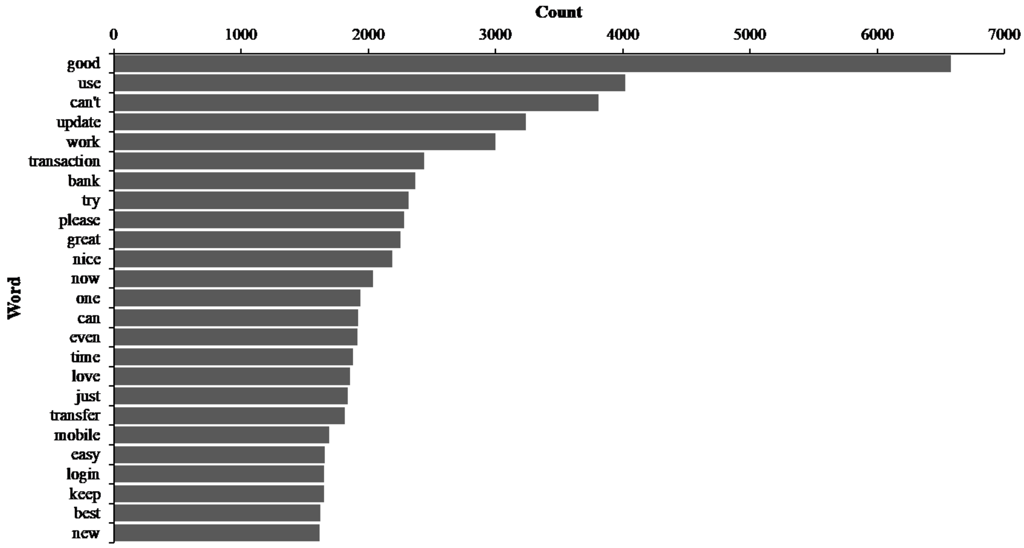

Figure 3: Top 25 frequent terms from full sample

To visualise the content of the reviews, we generate a word cloud shown in Figure 4. The word cloud presents a graphical representation of the most common terms in the corpus of 37, 460 reviews with the more prominent words represented by bigger-sized fonts. Consistent with the results presented in Figure 3, terms such as 'good', 'use', 'can't', 'update', 'transact', 'download', 'work', feature prominently. On the other hand, terms such as 'data', 'change', 'difficult', 'balance', 'code', 'connect', 'error', 'device', etc are less common.

Figure 4: Word cloud from full sample

It is expected that the hidden topics and sentiments analysed in this study will be driven by the words that are most frequent in the corpus. To identify the words driving the ratings assigned by users, word clouds are generated for the different user ratings as shown in Figure 5. Figure 5a shows that words such as ‘can’t’, ‘update’, ‘work’, ‘even’, ‘transact’, ‘download’, ‘poor’, ‘frustrating’, ‘error’, ‘log’, ‘worst’, ‘bad’, ‘upgrade’, ‘don’t’, etc are dominant in reviews corresponding to a user rating of 1.

The results for user ratings 1 and 2 are similar, except that words such as ‘please’, ‘make’, ‘can’, ‘transact’ are more common in the word cloud associated with user rating 2 (Figure 5b). To improve customer satisfaction and contribute to the financial inclusion efforts of the Central Bank of Nigeria, it is important that banks pay attention to user reviews associated with app ratings 1 and 2. Furthermore, results from the word clouds presented in Figures 5c to 5e show that reviews corresponding to higher user ratings are dominated by terms associated with positive sentiments. These include terms such as ‘good’, ‘great’, ‘nice’, ‘easy’, ‘excellent’, ‘love’, ‘awesome’, ‘cool’, ‘work’, etc.

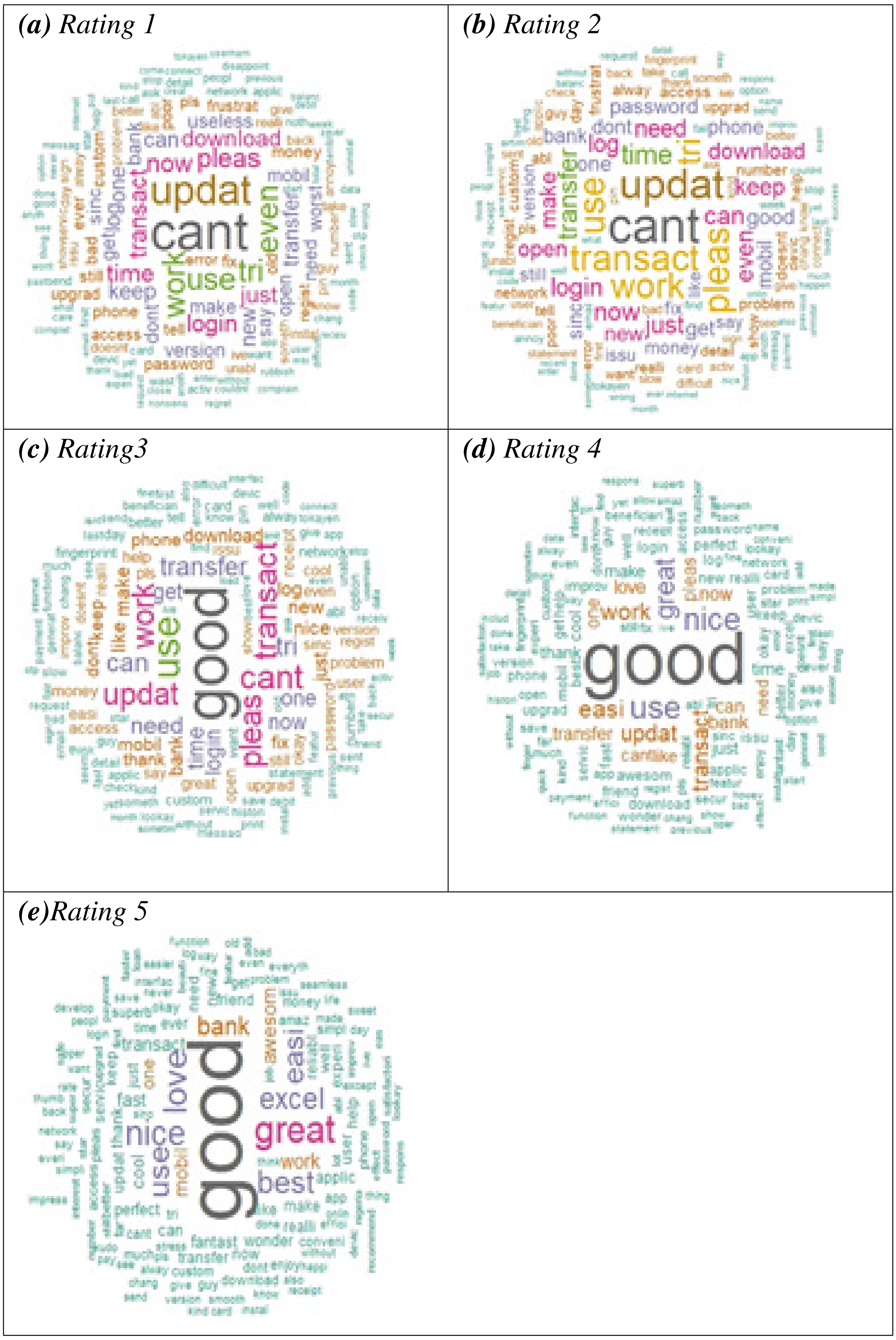

Figure 5: Word cloud by user rating

4.3 Analysis of Sentiments

The results of the sentiments expressed by mobile banking apps users are presented in Table 3. The analysis groups the sentiments into three categories – positive, neutral, and negative; but the study is principally interested in the positive and negative sentiments. Of the 239, 568 words analysed, about 17.8 per cent express positive sentiment while only 7.7 per cent express negative sentiment. These results are consistent with our earlier findings regarding the emotions of ‘trust’, ‘anticipation’, and ‘joy’ contained in our corpus.

Table 3: Sentiment analysis by bank authorisation category

Sample	Negative	Positive	Neutral	Total no. of words
Commercial Banks with International Authorisation (CBIA)	*7.9%*	*19.0%*	*73.1%*	134,364
Commercial Banks with National Authorisation (CBNA)	*7.4%*	*16.2%*	*76.3%*	102,594
Commercial Banks with Regional Authorisation (CBRA)	*6.3%*	*17.1%*	*76.6%*	732
Non-Interest Banks (NIB)	*5.5%*	*19.3%*	*75.2%*	1,878
All	*7.7%*	*17.8%*	*74.5%*	239,568

At about 19 per cent each, the reviews associated with mobile banking apps developed by non-interest banks (NIBs) and the commercial banks with international authorisation (CBIA) have the highest share of positive sentiments (Table 3). In other words, the NIB and CBIA recorded shares of positive sentiments that are above the value of 17.8 per cent recorded for the full sample. On the other hand, the mobile banking apps developed by commercial banks with national authorisation (CBNA) attract the least share of positive sentiments of about 16 per cent.The NIBs attracted the least negative sentiments of about 5 per cent.

In Table 4, the list of the top ten positive (42, 655 occurrences) and negative (18, 359 occurrences) sentiment terms contained in our full sample corpus with their frequencies and weights. As shown in Table 4a, the most common positive terms used by mobile banking apps users to describe their experience include: ‘good’, ‘work’, ‘great’, ‘love’, ‘nice’, ‘new’, ‘excellent’, ‘like’, and ‘thank’. The term ‘good’ with a weight of 0.15 is most dominant of the positive sentiment words.

Table 4: Top ten words with (a) positive sentiments and (b) negative sentiments

(a)			(b)		
Word	Freq	Weight	Word	Freq	Weight
good	6,578	0.154	please	2,284	0.124
great	2,253	0.053	bad	842	0.046
nice	2,190	0.051	useless	828	0.045
love	1,853	0.043	error	763	0.042
best	1,620	0.038	worst	748	0.041
new	1,616	0.038	poor	720	0.039
excellent	1,372	0.032	annoying	474	0.026
like	1,213	0.028	slow	466	0.025
thank	1,098	0.026	never	433	0.024

In contrast, Table 4b presents the most frequent negative sentiment words expressed by users to include: ‘please’, ‘problem’, ‘bad’, ‘useless’, ‘worst’, ‘error’, ‘poor’, ‘annoying’, ‘slow’, and ‘never’. While some of these terms derive from problems associated with poor information technology infrastructure, quite a number is also associated with poor customer service on the part of the banks. This point is underscored by reviews such as “Just pray not to have cash related issues with this bank. They will ignore you. Wished I never used them”. It is therefore important that the banks develop a mechanism for tracking user reviews of their mobile banking apps as much as they attend to in-person complaints received in their various branches.

Table 5: Polarity of reviews by bank authorisation category

Bank category	Average polarity	Sd. Polarity
All	0.395	0.609
Commercial Banks with International Authorisation (CBIA)	0.424	0.614
Commercial Banks with National Authorisation (CBNA)	0.345	0.598
Commercial Banks with Regional Authorisation (CBRA)	0.321	0.595
Non-Interest Banks (NIB)	0.474	0.564

The average polarity scores and the standard deviation (sd.) for the entire sample as well as the different categories of banks are presented in Table 5. Whereas a negative value of the average sentiment polarity implies a preponderance of negative sentiment terms and a positive value indicates the dominance of positive sentiment terms, the absolute value of the polarity score describes the sentiment intensity. The overall average sentiment polarity, which provides a summary measure of the sentiments is 0.395 (Table 5). In line with the results of the average user rating shown in Table 2, the mobile banking apps deployed by NIBs attracted the most positive average polarity score of 0.474 and the least uncertainty measured by the standard deviation regarding the polarity score (0.564). This is followed by the apps deployed by CBIA banks with an average polarity score of 0.424. However, at 0.614, the standard deviation associated with the sentiments expressed by users of mobile banking apps deployed by the CBIA is relatively high. The least average polarity score is recorded by CBNA's mobile banking apps. These results highlight the need for banks with low average polarity scores to invest more in their mobile banking platforms if they must remain competitive.

4.4 Analysis of Emotions

To further understand the results presented in Section 4.3, the emotions expressed by the bank customers are analysed. The results show a total of 91, 137 emotive words in the corpus. The eight types of emotions allowed for by the NRC dictionary, namely: 'trust', 'anticipation', 'joy', 'surprise', 'sadness', 'fear', 'anger', and 'disgust' and their respective shares are shown in Figure 6. The three most dominant emotions are 'trust', 'anticipation', and 'joy'. These three categories of emotions are largely positive and they jointly account for about 66 per cent of the total emotions expressed by mobile banking apps users in Nigeria. The 'trust' emotion, which accounts for about 28 per cent, reflects the users' belief in the ability and reliability of their respective mobile banking apps.

The second dominant emotion of 'anticipation' (accounting for 19 per cent) indicates that a substantial number of users expect that the mobile banking apps will continue to deliver the required services. The 'joy' emotion, which accounts for about 18 per cent of the total emotive words implies that approximately 18 times out of 100, users express a feeling of happiness based on their experience with their mobile banking app. The 'surprise' emotion accounts for about 10 per cent of the emotive words detected in the corpus. It is important to note that this category of emotion represents a feeling of unexpectedness or shock, which may either be pleasant or unpleasant.

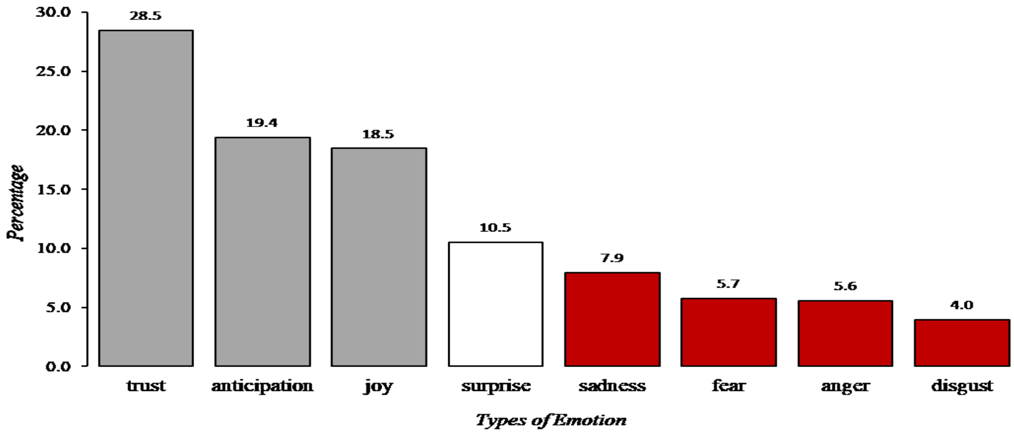

Figure 6: Distribution of emotions from full sample

The less dominant emotions relate to 'sadness', 'fear', 'anger', and 'disgust'. These emotions have a combined share of about 23% of the emotive words. The terms accounting for these categories of unpleasant emotions include 'bad', 'waste', 'refuses', 'error', 'frustrating', 'annoying', 'ignore', 'never', 'worst', etc. These terms are associated with user complaints regarding either their inability to download the mobile banking apps or the failure of the apps to provide the required services. An example of a review with such unpleasant emotion in the corpus reads as follows: "very bad app. I just wasted my subscription on this app, I tried opening it many times, but it was not functioning well. Don't download please".

Table 6: Analysis of emotions by bank authorisation (%)

Emotion type	CBIA	CBNA	CBRA	NIB
anger	5.0	6.4	3.6	2.9
anticipation	19.4	19.3	20.2	19.3
disgust	3.9	4.2	2.7	1.6
fear	5.4	6.4	3.6	4.1
joy	19.0	17.6	17.9	21.1
sadness	7.4	8.8	5.4	6.7
surprise	11.3	9.3	7.6	9.8
trust	28.6	28.1	39.0	34.5

Furthermore, the emotions generated for the mobile banking apps deployed by the different categories of banks operating in the country were analysed. As shown in

Table 6, the ‘trust’ emotion is dominant across the four categories of banks, with regional banks’ (CBRA) recording the highest share of about 39 per cent and the national banks (CBNA) having the least (28.1 per cent). For commercial banks with international, national, and regional authorisations, the second dominant emotion is ‘anticipation’. Interestingly, the second dominant emotion for non-interest banks (NIB) is ‘joy’ followed by ‘anticipation’. Thus, the ‘joy’ emotion is highest in the order of NIB, CBIA, CBRA and CBNA.

In terms of the less pleasant emotions expressed by users, the results show that the emotions of ‘anger’ and ‘disgust’ are highest under the CBNA category and least under the NIB category. In other words, users of mobile banking apps deployed by the NIBs are least angered and disgusted with their apps. Customers of CBNAs are most ‘fearful’ of getting the desired services from their mobile banking apps while CBRA customers are least fearful. Similarly, the emotion of ‘sadness’ is highest under CBNA and least under the CBRA.

4.5 Topic Analysis

This section shows the results of the topic model estimated to uncover the hidden topics in the corpus. For ease of interpretation, we heuristically choose five (5) as the number of topics present in the corpus. Based on the most probable terms contained under each topic, labels are assigned to the identified topics. As shown in Table 7, topic 2 has the highest weight in the corpus with a gamma value of 0.302. The terms occurring under this topic with relatively high probabilities include: ‘good’, ‘use’, ‘work’, ‘nice’, ‘can’, etc. Therefore, the study describes topic 2 as capturing user experience with app functionalities. The next dominant is topic 5, with a gamma value of 0.258 and common words that include ‘update’, ‘trying’, ‘love’, ‘good’, ‘nice’, ‘download’ etc. Therefore, a label ‘user satisfaction with successful app updates’ was intuitively assigned to the topic.

Table 7: Identified topics and their weights

s/n	1		2		3		4		5	
	Gamma=0.220		Gamma=0.302		Gamma=0.100		Gamma=0.120		Gamma=0.258	
	term	beta	term	beta	term	beta	term	beta	term	beta
1	bank	0.0276	good	0.0551	use	0.0284	transact	0.0322	update	0.0318
2	can't	0.0242	use	0.0295	can't	0.0263	can't	0.0308	try	0.0203
3	work	0.0234	work	0.0169	good	0.0174	update	0.0210	love	0.0184
4	even	0.0187	nice	0.0145	don't	0.0160	try	0.0146	good	0.0180
5	great	0.0165	can	0.0145	can	0.0154	transfer	0.0142	nice	0.0134
6	good	0.0119	great	0.0142	transfer	0.0142	make	0.0133	time	0.0125
7	password	0.0112	please	0.0120	now	0.0121	good	0.0130	now	0.0121
8	please	0.0104	mobile	0.0109	make	0.0114	new	0.0124	login	0.0121
9	easy	0.0097	one	0.0106	even	0.0108	use	0.0123	please	0.0108
10	now	0.0089	can't	0.0100	new	0.0106	need	0.0121	phone	0.0091
11	best	0.0088	login	0.0089	keep	0.0104	download	0.0108	keep	0.0090
12	just	0.0085	open	0.0086	one	0.0092	love	0.0104	like	0.0085
13	money	0.0083	will	0.0085	fix	0.0090	one	0.0094	download	0.0084
14	new	0.0083	transfer	0.0077	password	0.0083	just	0.0083	use	0.0084
15	need	0.0083	transact	0.0072	phone	0.0075	phone	0.0079	since	0.0084
16	excellent	0.0080	easy	0.0072	try	0.0074	keep	0.0075	one	0.0083
17	login	0.0078	still	0.0071	download	0.0074	time	0.0072	just	0.0082
18	application	0.0075	get	0.0071	time	0.0073	easy	0.0072	excellent	0.0078
19	will	0.0073	bank	0.0070	bank	0.0071	useless	0.0066	transaction	0.0077
20	keep	0.0067	just	0.0070	application	0.0068	fix	0.0066	best	0.0073
Assigned topic	*Feedback on banks' responsiveness to user observations*		*User experience with app functionalities*		*Operational failures associated with the apps*		*Challenges faced by users with app upgrades*		*User satisfaction with successful app upgrades*	

The third dominant topic (topic 1) features terms such as 'bank', 'can't', 'work', 'even', 'great', 'good', 'password' and has a gamma value of 0.220. Consequently, a label that describes the responsiveness of the banks to issues arising from the use of their apps was assigned. The last two topics relate to the challenges faced by users in the process of installing updated version of their mobile banking apps (topic 4, gamma=0.120) and the operational failures associated with the mobile banking apps (topic 3, gamma=0.100). These results imply that conversations relating to the satisfaction derived from using mobile banking apps were more dominant, compared to the issues relating to the logistics of using the apps and their updates.

5.0 Conclusion and Policy Recommendations

This paper analyses reviews written by users of mobile banking apps in Nigeria to derive useful insights regarding the sentiments and emotions expressed by the users. The textual data comprises 37, 460 reviews mined from iOS- and Android-based mobile banking apps deployed by twenty-two banks operating in Nigeria. The study argues that beyond operational benefits, an analysis of the feedback provided by users of mobile banking apps is useful for a number of reasons, including the enhancement of payments system stability as well as the promotion of financial inclusion.

The study documents a number of interesting results. First, most of the users of mobile banking apps are quite satisfied with their mobile banking experience based on the average rating assigned to the apps. About 51 per cent of the users assigned the highest ranking of 5 while only about 27 per cent assigned the least ranking of 1. The average ratings for the mobile apps deployed by non-interest banks and the banks with international authorisation are above the industry average while the apps for banks with national authorisation record the least average rating. Second, the most frequent term contained in the corpus is ‘good’ indicating that a preponderance of users adjudged their apps functional enough for their mobile banking requirements. Third, reviews associated low ratings (app ratings 1 and 2) are dominated by words such as ‘can’t’, ‘update’, ‘transaction’, ‘work’, ‘please’, ‘download’, ‘use’, and ‘transfer’. It is important that banks whose apps account for a greater share of the low ratings pay attention to challenges relating to apps updates, failed transactions, and other unpleasant experiences documented in the user reviews.

Fourth, the corpus is dominated by positive sentiments with the demonstrated emotions ranging from ‘trust’ to ‘joy’. The corpus for non-interest banks recorded the highest share of positive sentiments, followed by banks with international authorisation. The most frequent words driving the positive sentiments expressed by the users include ‘good’, ‘work’, ‘great’, ‘nice’, ‘love’, ‘best’, ‘new’, and ‘excellent’, among others. Lastly, the results show that the topics in the corpus can be captured under 4 main themes, which relate to: the description of user experience with app functionalities, feedback on banks’ responsiveness to user observations, operational failures associated with the mobile banking apps, and the issues relating to app updates. We recommend for banks to continue to educate users on the existing functionalities of their apps while also ensuring that they respond to user complaints promptly and effectively. It is hoped that future research efforts would throw more light on the issues identified in this paper by (i) studying the evolution of user sentiments over time in a manner that accounts for the rapidly changing technological landscape in the financial industry, and (ii) utilising primary data obtained from a structured survey to further analyse user satisfaction under a setting that allows for parametric analysis.

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Appendix 1: Summary of selected studies

Author	Literature strand	Method of Analysis	Key findings
Bankole *et al.* (2011)	Determinants of mobile banking adoption	Regression analysis of survey data	Based on a survey of 231 users, study identified culture as an important factor in the usage and adoption of mobile banking in Nigeria.
Odumeru (2013)	Determinants of mobile banking adoption	Regression analysis applied to primary data	Factors that determine mobile banking usage in Nigeria include its relative advantage over other solutions, complexity of the system, compatibility with the circumstances of the user, and the visibility of its benefits.
Agwu and Carter (2014)	Determinants of mobile banking adoption	Thematic analysis of survey data	Based on focus group discussions and interviews, study showed that adoption of mobile banking in Nigeria is a function of by customers' level of awareness, convenience of use, security, cost of transaction compared to other alternatives.
Ifeonu and Ward (2015)	Determinants of mobile banking adoption	Technology acceptance model applied to primary data	Trust is key to the adoption of mobile banking. Confidentiality, integrity, authentication, access control, and best business practices matter for mobile technology trust in Nigeria.
Khan and Ejike (2017)	Determinants of mobile banking adoption	Logistic regression applied to survey data	Based on a survey of 400 people in Nigeria, study found that mobile banking adoption is determined by people's literacy level, versatility of the system, and convenience of use.

Appendix 1 contd.: Summary of selected studies

Author	Literature strand	Method of Analysis	Key findings
Contini *et al.* (2011)	Regulatory oversight and security issues in mobile banking and payments	Review of literature	The development of an appropriate regulatory oversight model by both bank and non-bank regulators is key for a successful mobile payment system. Such joint efforts are also helpful in clarifying compliance responsibilities.
Chatain *et al.* (2011)	Regulatory oversight and security issues in mobile banking and payments	Review of literature	Countries must ensure an enabling AML/CFT legal and regulatory framework that is comprehensive, sound, clear, non-discriminatory, and proportionate. Policy makers are to also promote frameworks that balance financial inclusion objectives with financial integrity and encourage inter-agency coordination.
Khiaonarong (2014)	Regulatory oversight and security issues in mobile banking and payments	Review of international experience	To preserve public confidence in mobile payments system and enhance financial stability, financial authorities should implement oversight measures such as: an explicit legal regime; anti-money laundering & countering the financing of terrorism measures for preventing financial integrity risks without stifling innovation; fund protection measures such as pass through deposit insurance; contingency plans for operational disruptions; and risk controls in payment systems.

Appendix 1 contd.: Summary of selected studies

Castle *et al.* (2016)	Regulatory oversight and security issues in mobile banking and payments	Systemic threat model	Security vulnerabilities in digital financial ecosystem is not as bad as it is often portrayed. While evidence of attack vectors is found in several mobile banking apps, service providers are generally aware of the threats and making "security-conscious decisions".
Reaves *et al.* (2017)	Regulatory oversight and security issues in mobile banking and payments	Automated analysis	Based on an evaluation of the security features of selected mobile money services applications, it was shown that significant vulnerabilities exist. It argued that substantial improvements are required to ensure that app users and their funds are protected.
Jack and Suri (2011)	Economic impacts of mobile banking services	Analysis of survey data	Mobile money helps in facilitating trade, increasing household savings, improving resource allocation, and promoting informal risk-sharing in Kenya.
Adewoye (2013)	Economic impacts of mobile banking services	Non-parametric statistical tests applied to primary data	The introduction of mobile banking helps Nigerian banks to improve the quality of service offered to their customers; thus, leading to higher customer satisfaction.

Appendix 1 contd.: Summary of selected studies

Mbiti and Weil (2015)	Economic impacts of mobile banking services	Fixed effect instrumental variable regression	Mobile money (M-Pesa) reduces the cost of money transfers in Kenya, generates vertical integration benefits, increases the efficiency of the banking system, broadens financial inclusion, and leads to increase in bank use, savings and employment.
Okon and Amaegberi (2018)	Economic impacts of mobile banking services	Panel analysis	Mobile banking and other electronic payment channels boost bank's profitability in Nigeria.
Ozili (2018)	Economic impacts of mobile banking services	Review of literature	Digital finance impacts positively on financial inclusion and financial stability. The convenience associated with the use of digital finance is particularly of benefit to individuals with low and variable income.
Aron (2018)	Economic impacts of mobile banking services	Empirical literature review	Mobile money promotes financial inclusion and fosters risk-sharing in the informal sector through the reduction in transaction costs of domestic transfers.
Bongomin *et al.* (2018)	Economic impacts of mobile banking services	Graphical method	Mobile money as well as the existence of social networks among users promote financial inclusion in rural Uganda
Wieser *et al.* (2019)	Economic impacts of mobile banking services	Intention to treat model using panel data	Mobile money improves livelihoods in poor and remote settings of Uganda. It increases self- employment, reduces food insecurity, and reduces the cost of remittance transactions.

Appendix 1 contd.: Summary of selected studies

Patnam and Yao (2020)	Economic impacts of mobile banking services	Regression discontinuity design	Use of mobile money services improves the resilience of households to shocks, helps firms improve their sales, and creates greater future sales optimism amongst firms in India.
Aggarwal *et al.* (2020)	Economic impacts of mobile banking services	Randomised control trial	The use of mobile money services facilitates savings amongst individuals and microentrepreneurs in Malawi
Olaleye *et al.* (2017)	Analysis of user experience	Partial least squares applied to primary data	Dimensions such as privacy, security and convenience contribute positively to the experience of users while anxieties relating to the use of mobile apps contributes negatively.